Assessment of the cost and environmental impact of demand side management on residential sector

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Assessment of the Cost and Environmental Impact of Demand Side Management on Residential Sector

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***Abstract*—The paper presents a detailed study of the potential impact on the cost and greenhouse gas emissions (GHG) through low voltage (LV) residential demand-side management (DSM). The proposed optimisation algorithm is used to shift non-critical residential loads, wet load category is used as a case study, in order to minimise the total daily cost and emissions of GHG due to generation. This study shows that it is possible to reshape the total power demand and reduce the cost of demand and gas emissions to some extend. It is also shown that further optimisation of the cost leads to an increase of the gas emissions because of their conflicting nature.**

***Keywords*—Demand Side Management, optimisation algorithm, load modelling, residential load, low voltage.**

I. Introduction

Customers' interest on the reduction of the cost of the daily power demand has increased. This cost does not describe only the price of electricity, but also the environmental cost (defined in this paper by generation greenhouse gas emissions (GHG)). One method of altering the cost to the consumer is load manipulation through the actions of demand side management (DSM), which will impact on multiple aspects of the supply of electrical energy.

There have been several studies on DSM strategies, and their impact on energy demand, that are not directly connected to pricing or environmental causes, e.g. [1], [2], [3], [4], [5]. In the majority of these studies, the analysis is performed at higher voltage levels and loads are treated as aggregate amounts of energy, rather than as discrete appliances with operation cycles. However, this approach is not appropriate for the analysis of low-voltage (LV) networks, where many proposed DSM actions will be implemented.

At the LV level, the domestic energy demand depends on the mixture of the individual electrical appliances, the behaviour of the residential users and environmental aspects (e.g. external temperature). It is the combination of these three factors which results in the stochastic nature of LV power demand and requires more detailed simulation techniques than those typically applied at the higher voltage levels. This generally requires consideration of the specific loads available for DSM, as load management must not impact on users' quality of life. The available loads, termed as 'non-critical', may be rescheduled without affecting the users. This is demonstrated in several studies that focus on specific load categories and examine how their manipulation could reduce the cost or the GHG emissions, e.g. electric vehicles (EV) and heat pumps [6], [7]. However, the analysis methods for EVs and heat pumps allow for interruption of their operation. As this is not true for most domestic appliances, the techniques are not directly transferable.

In this paper, an approach for DSM implementation on the LV residential load is presented, which includes consideration of device operation cycles. This employs a multi-objective optimisation algorithm in order to achieve the least economic and environmental cost of required daily energy with the minimum effort. The effort is defined as the percentage of the load that is required to be managed [8]. In order to calculate this, detailed residential load models are used to identify the use of 'non-critical' loads. The load models are then combined with typical profiles of cost and GHG emissions in the UK to reform the power demand.

The paper is structured as follows: in the first Section an overview of the proposed methodology is presented, followed by the problem formulation in Section II; Section III describes the properties of the optimisation algorithm; in Section IV, the case study is described and the results of the application of the methodology are presented and discussed; conclusions and suggestions for further work are given in Section V.

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II. Problem formulation

In practice, LV residential load consists of the various appliances that exist in households and can be divided into two categories according to their necessity: critical and non-critical loads. Although the use of critical loads cannot be modified without changing the behaviour of household occupants, non-critical loads can be deferred so as to achieve the desired targets. An example of non-critical load category is wet loads, such as dishwashers, washing machines tumble dryers and washing dryers. The operation of these loads can be postponed for some other time during the day if needed without noticeable obstruction to the users. Wet loads are responsible for large percentage of the total daily power consumption (approximately 15%) for the UK [9]. The management of such loads can create significant difference on the total power demand, the cost of it to the customers and the total daily GHG emissions.

The calculation of active power demand before and after the load shifting requires the development of detailed power profiles of individual households to increase the accuracy of the results. In this paper, a previously developed combined Markov chain Monte Carlo model is implemented to simulate the UK residential demand, further details are available in [10]. The detailed profiles allow for realistic representation of the use of all residential appliances, including the wet loads, by the UK population.

III. Methodology

The proposed methodology consists of a multi-objective optimisation algorithm for shifting the wet load category during the day. The objectives of the study are to minimise the total daily cost of the power demand to the end user and the amount of GHG emissions that derive from supplying the power demand simultaneously. In order to achieve these targets, the electricity price and GHG emissions profiles are combined in the optimisation algorithm and used as the drivers of the DSM actions on wet loads. A significant parameter is the estimation of the minimum number of shifted loads that are required for the best result.

A. Optimisation problem definition

The objective functions of the proposed algorithm can be described mathematically by the Eq. (1-2).

$$min(\sum_{i=1}^{t} c_{comb} = \sum_{i=1}^{t} x * c_{wi} + y * em_{wi}) \tag{1}$$

$$min(n_{swl}) \tag{2}$$

where t defines the time steps, which in this study is equal to 1440, c_{comb} is the combined cost and is calculated by c_{wi} and em_{wi} which are the weighted values of the price and GHG emissions respectively. They are defined in Eq. (3-4). The weighting factors x and y are used to control the level of impact of each criterion. n_{swl} is the number of the shifted operations.

$$c_{wi} = \frac{(c_i * P_i) - min(c_i * P_i)}{max(c_i * P_i) - min(c_i * P_i)} \tag{3}$$

$$em_{wi} = \frac{(c_{em} * em_i * P_i) - min(c_{em} * em_i * P_i)}{max(c_{em} * em_i * P_i) - min(c_{em} * em_i * P_i)} \tag{4}$$

where c_i, em_i and P_i describe the price in $£/MWh$, the GHG emissions in tonnes of CO_2 eq./MWh and the active power demand in MWh for each time step i respectively. The average cost of the GHG emissions c_{em} is equal to £33/tonne of CO_2 equivalent [11].

There are some constraints that need to be taken into consideration. The proposed load management includes only load shifting and, thus, the daily energy should remain the same before (E_{old}) and after (E_{new}) the manipulation.

$$E_{new} = E_{old} \tag{5}$$

Also, in the new load curve, the peak of power demand should be lower than the old load curve. The variation of new demand during the day should be smaller in order to avoid the possibility of concentrating all the shifted load within a short period of time.

$$P_{maxnew} < P_{maxold} \tag{6}$$

where P_{maxnew} and P_{maxold} are the peak values of active power profile.

One more limitation is that the reconnection time should not be among the two peak time slots, defined in this paper as the morning peak between 08:00 - 10:00 and the evening peak during 18:00 - 22:00 based on the typical UK residential load curve.

$$i_{st} \notin [T_{peak}] \tag{7}$$

where i_{st} is the time step when the shifted load cycle is starting and T_{peak} include the periods of peak demand as defined above.

Finally, one restriction that differentiates this case from the studies on loads such as EV, is that wet loads operate in cycles which require they will start and finish without interruption. Also the operation cycles are fixed in length and magnitude.

B. Optimisation algorithm

The price and emissions profiles are very important in the load shifting process as they define the disconnection t_{disc} and reconnection t_{rec} time step. Their direct correlation, even after the conversion of the GHG emissions profile into the equivalent cost that derives from it, is not possible because of the different scales. In order to be able to control the level of effect of each driver, both profiles are multiplied with the total power demand and then normalised. The profile that occurs is the combined cost c_{comb}, as can be seen from Eq. (1), (3) and (4).

The t_{disc} is set by the time of day when the maximum c_{comb} occurs and the wet load occurrences of this time are selected for shifting. If no wet load is present during the time of maximum c_{comb}, the nearest operation cycle is selected and used to define the t_{disc}. The time step of load reconnection t_{rec} is defined so as to achieve the targets above without violating the constraints. To fulfill this, the inverse of the c_{comb} is used to calculate the discrete cumulative probability. The t_{rec} is selected stochastically based on this probability. The result of that is to distribute the shifted loads more uniformly across the period that is considered as appropriate for reconnection and avoid the creation of a new peak.

IV. Case Study

The methodology above is applied on 7,600 households, 20 LV highly urban groups of 380 households each, to represent the total loading of a typical medium voltage transformer.

Five cases are considered to study the sensitivity of the effect of the two drivers on the impact on the aggregate power demand. In the first case, only the financial criterion is taken into account, while the GHG emissions driver is ignored. The percentage of the electricity price driver reduces gradually, while the significance of the environmental criterion increases until the financial criterion reaches 0% (Table I).

TABLE I. The selected test cases on which the optimisation algorithm is applied

Test case	Financial criterion contribution - x	Environmental criterion contribution - y
Case 1	1	0
Case 2	0.75	0.25
Case 3	0.50	0.50
Case 4	0.25	0.75
Case 5	0	1

A. UK residential load

The individual demand profiles have been selected to simulate the typical UK households based on the overall demographic characteristics of the UK population [10]. The winter weekday has been selected as the time of the simulation as it is the period that the use of wet loads is most frequent [12]. The contribution of the wet load category on the aggregate power demand of the selected group is illustrated in Fig. 1. It is obvious that the two peaks of the power demand of wet load category coincide approximately with the peaks of the total household demand.

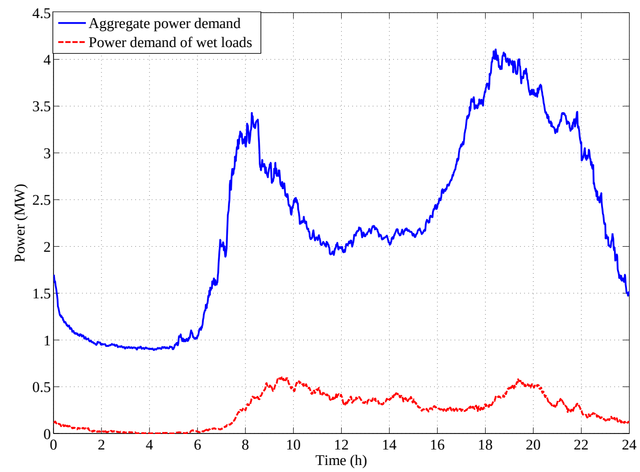


Fig. 1. Power demand of wet loads and the total household demand.

B. Generation price and GHG emissions

Fig. 2 presents the UK daily profiles of price [7] and GHG emissions for a typical winter weekday which are defined by the operating mixture of generation units at each time of day.

Although the cost of electricity for the user is a combination of a number of factors, it mostly derives from the cost of generation. For the purposes of this paper, the average electricity price is used. This depends on the contribution of all types of generation plants and remains constant due to long term contracts. Also, the electricity price is mostly formed by the power plants that work with mineral fuels because of their high price, such as oil and coal. Any load shifting of this magnitude will create changes on the generation of these plants as they respond faster to the demand changes. For these reasons, the average values of price can be used instead of the marginal values. In Fig. 2, the price of electricity increases during most of the daytime, while the electricity is cheaper during the night highlighting the need of decongestion of the daytime load.

The GHG emissions are the marginal emissions derived from operational data of generation plants on the British grid [13]. Marginal data is required because the shift in non-critical loads will not affect the operation of baseload plants, only those operating on the margin, which tend to have higher GHG emissions intensities. Multiple linear regression was used to determine the marginal emissions factors at different times of day for a typical winter day between November 2008 and January 2013. The method was based upon that developed by Hawkes [14] and is described in greater detail in [15]. It can be seen in Fig. 2 that the marginal GHG emissions fluctuate throughout the day, but tend to be higher at times of low demand. This is likely to be due to coal-fired plants being the marginal generators at these times, while gas-fired power stations (which have lower GHG emissions) are the marginal generator at times of high demand. This relationship is mostly determined by the relative prices of coal and gas, suggesting that coal has generally been cheaper than gas.

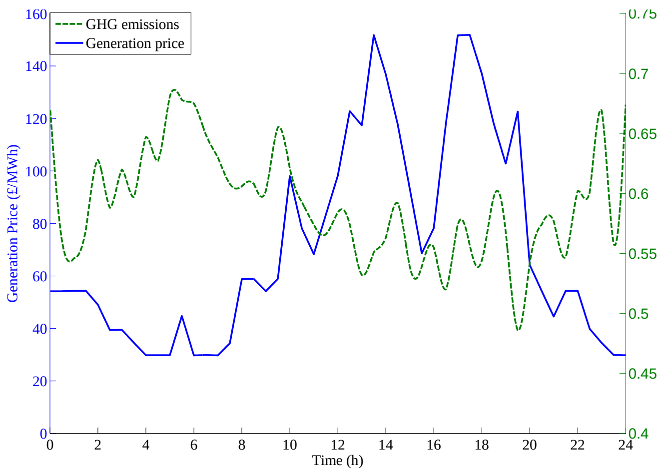


Fig. 2. Daily profiles of price and GHG emissions per MWh [7], [15].

Fig. 3 depicts the normalised cost that combines the price of electricity and the equivalent cost of the GHG emissions for each case according to Eq. (1), (3) and (4). It can be seen that the profile of price dominates and affects the combined cost despite the normalisation and its low contribution.

C. Results

The results of the optimisation algorithm on the selected cases are presented here. In Fig. 4(a), the change in combined cost for each shifted operation cycle of the wet loads is presented while the black dots indicate the number of required cycle shiftings to achieve the minimum combined cost. Fig. 4(b) shows that in all cases, even when the contribution of electricity price is either small or zero, there is some reduction in cost and the minimum total cost is reached after approximately 5140-5300 shiftings depending on the case. Also, it is

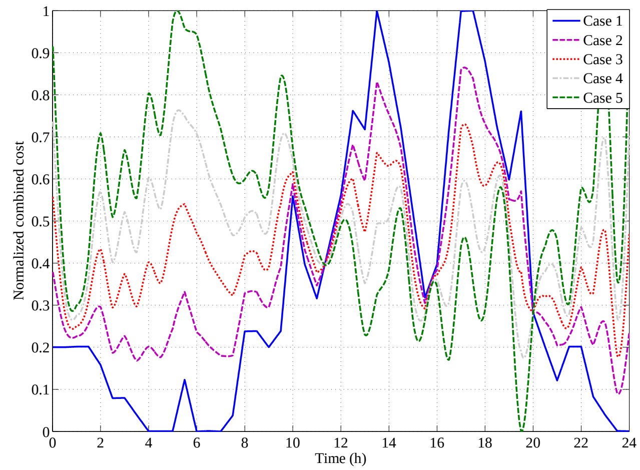


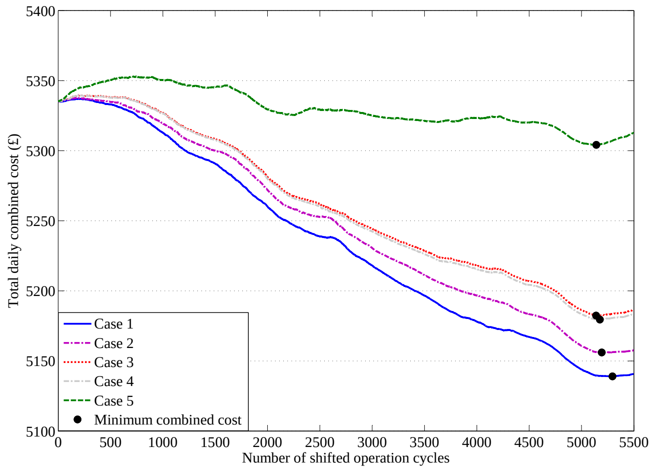
Fig. 3. The normalised combined cost profile for each case according to Eq. (1), (3) and (4).

clearly seen that the price has greater influence on the combined cost than GHG emissions despite the equal weighting (case 3) as observed in Fig. 3

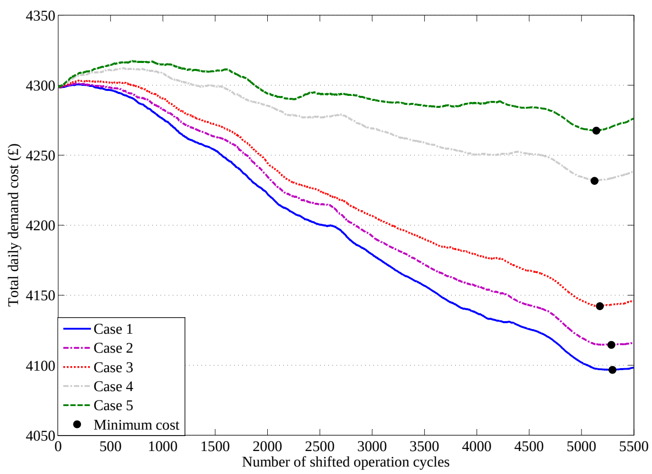
The effect on the marginal GHG emissions, as it is presented in Fig. 4(c), is interesting. The GHG emissions in cases 2 and 3 remain almost constant for approximately 1500 shiftings and then actually increase, while, on the other hand, it can be seen that it is possible to reduce the emissions in cases 4 and 5 for the first 3500 shiftings. The maximum savings occur at 2000 shiftings in case 4 and 1500 shiftings in case 5.

Further details are presented in Fig. 5(a), which shows how the power demand of the load category of the wet appliances reshapes after the management technique is applied in all cases. Intuitively, in the cases where the weighting favours cost over GHG emissions, it is observed that the operation of the wet loads is limited during the daytime when the electricity is more expensive and the majority of the wet load has been shifted towards the night-time. However, the increased consumption during early in the morning is the reason behind the increase of the amount of emissions in these cases (Fig. 4(c)). In cases 4 and 5, the increased influence of GHG emissions on the combined cost is perceptible on the new power demand curves. Also, it is clear that the increased demand after midnight (00:00-04:00) reduces the electricity price enough to cover the cost of the demand during daytime when electricity is more expensive, this explains the fact that the total cost reduces in case 5 (Fig. 4(c)). The result of avoiding the reconnection of loads during peak hours is also visible.

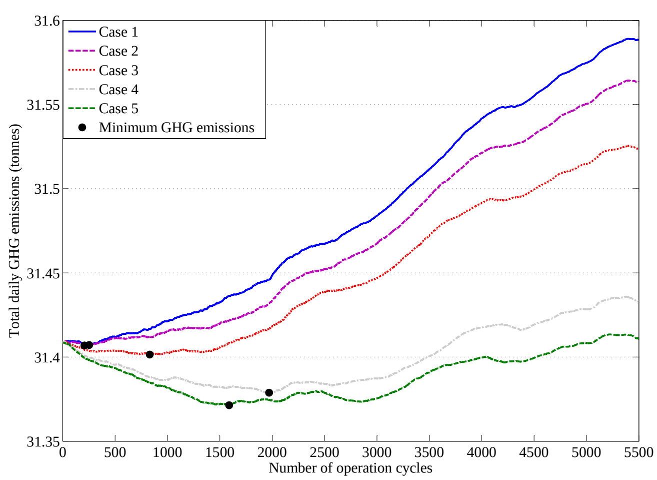
Fig. 6 also shows that the maximum reduction on the combined cost reached about 3.7%. However, the individual savings on total daily cost and the GHG



(a) Total combined cost



(b) Total price



(c) Total GHG emissions

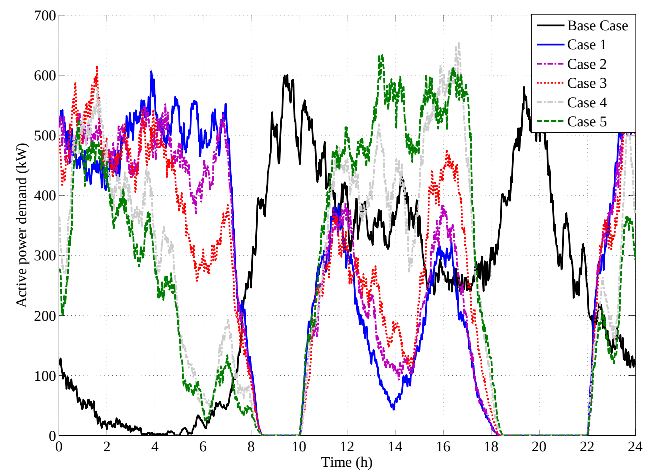
Fig. 4. Differentiation of total combined cost, price and GHG emissions according to the number of load shiftings for each case.

emissions reached about 4.7% and 1%, respectively. This shows the attempt of the code to balance the two drivers, despite the greater influence of price. Further details on the savings for each case are presented in Table II.

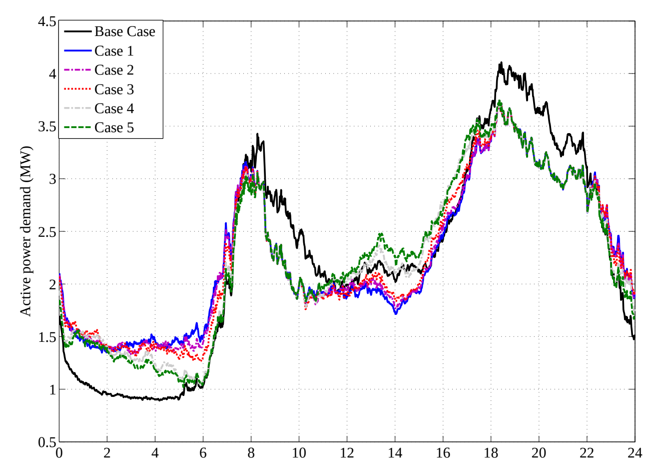
TABLE II. THE SAVINGS AMONG THE TEST CASES

Test Case	Total combined cost savings	Total cost savings	Total GHG emissions savings
Case 1	3.7%	4.7%	N/A
Case 2	3.4%	4.4%	N/A
Case 3	2.9%	3.6%	N/A
Case 4	2.9%	1.5%	0.8%
Case 5	0.6%	1%	1%

The effect of the reformed power curve of the wet loads on the aggregated power curve is demonstrated in Fig. 5(b). The power during the peak hours has reduced from 8.5% to 8.9% in the evening and 7.8% to 10.9% in the morning which will help to alleviate stress in the electrical network. The power during night time has a significant increase which varies between 5 and 50%, according to the case and time. The power demand decreases during midday for cases 1-3 and increases for cases 4 and 5 showing the influence of the weighting between the financial and environmental criteria.



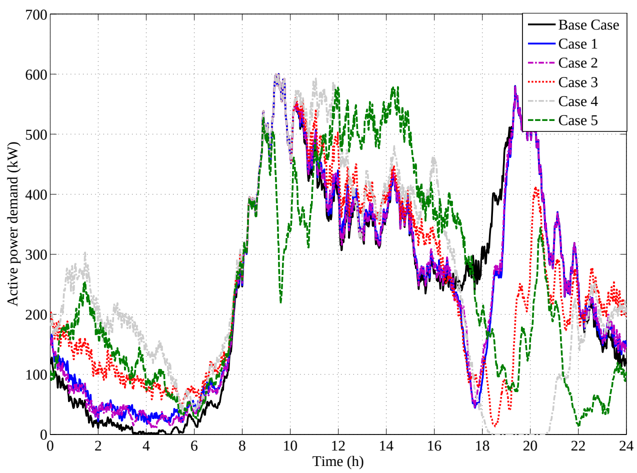
(a) Active power demand of wet loads



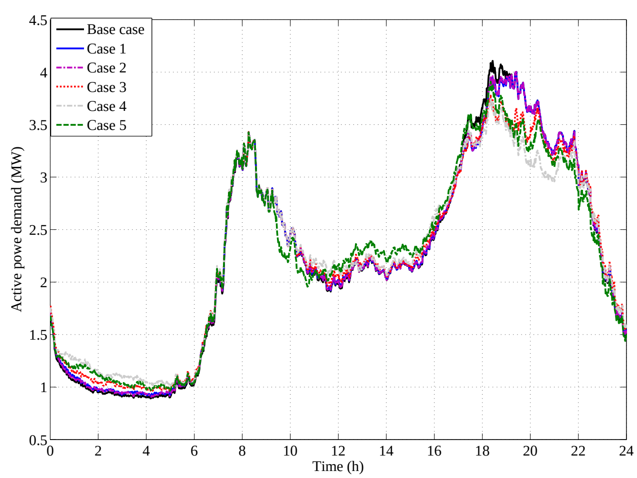
(b) Daily active power profile

Fig. 5. Active power demand of the wet loads and total residential demand before and after load shifting for minimum daily cost.

As mentioned previously, the maximum savings of GHG emissions occur after a low number of shiftings, from 250 to 1970 varying between the test cases. Fig. 6(a) and 6(b) present the differentiation of power demand on wet load and the aggregate load after those shiftings. Although the number of shifted operations is small, it is enough to observe the operation of the algorithm: up to this point, the operation cycles are moved to achieve both targets (cases 2-4). Loads are disconnected from the evening peak and reconnected at night. In this way, both the emissions and the cost reduce, resulting in the relief of the evening peak.



(a) Active power demand of wet loads



(b) Daily active power profile

Fig. 6. Active power demand of the wet loads and total residential demand before and after load shifting for minimum GHG emissions.

V. Conclusion

This paper has shown that management of LV loads allow for significant reductions in cost and GHG emissions. The presented results combine the average values of electricity price and the marginal price of GHG emissions with detailed models of LV residential loads through a multi-objective optimisation algorithm. The results show that the financial factor has a greater impact in shaping the combined total cost, which may explain the current situation of generation, where price is the main objective and GHG emissions become difficult to decrease.

The volume of reductions suggest that DSM actions on non-critical loads applied on LV level and in larger scale can lead to reductions in price and GHG emissions comparable to those achieved by distributed generation (DG). In the future, larger group of households could be used to investigate this possibility. Also, a network analysis could be performed to study the reaction of the network characteristics on this DSM actions and any further potential benefits.

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